FLUSHING UNDER SOURCE UNCERTAINTIES

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Abstract

Upon determination of a possible contamination threat in a water distribution network, a variety of response actions (e.g., public notification and operational changes) can be pursued in order to minimize public health and economic impacts and ultimately return the utility to normal operations. Flushing is a relatively common operational response option employed by utilities to address water quality concerns. Previously, an optimal hydraulic response tool was developed to help identify the best hydrant locations to flush. However, in order to apply this tool the contaminant injection location needs to be known. In previous research efforts, either the injection location was assumed to be known, or a sensor coverage map, which displays all contamination incidents potentially detected by a sensor, was employed to identify all possible injection locations. While the flushing locations selected for a known source location were effective in reducing impacts, the locations selected based on sensor coverage maps were not as effective. Therefore, in this study, a source location algorithm based on an event backtracking analysis is used to identify the most likely source locations. An example network model and multiple injection locations are used to evaluate the effectiveness of this approach. In addition, the reduction in impacts between the three different source identification approaches (i.e., known, sensor coverage map, backtracking) were compared. Overall, knowing the contaminant injection location greatly influences the effectiveness of the flushing response. For this study, the smaller amount of possible source locations, the greater the reduction in impacts. If only one source location is identified, the impact reduction could be as high as 98%. However, when 18 possible sources were identified from the sensor coverage map approach, only a reduction of 2% was achieved.

Keywords

Water distribution systems, contamination events, backtracking, event detection, flushing, response, water security

1. INTRODUCTION

Since the events of September 11, 2001, water utilities have had increasing concerns about water quality and the possibility of accidental or intentional contamination events within a distribution network. The U.S. EPA's Response Protocol Toolbox (U.S. EPA, 2003) provides recommendations on actions that water utilities can take to minimize potential impacts to consumers following a contamination threat. Detection, source identification, and consequence management are major steps in this protocol. Recent research efforts to aid in the first step, detection, have focused on the placement of online water quality monitoring sensors that together form a contamination warning system (CWS) (Kumar et al., 1997; Kessler et al., 1998; Ostfeld and Salomons, 2004; Berry et al., 2006; Propato, 2006; Murray et al., 2008; Ostfeld et al., 2008; Murray et al., 2010). The overall goal of a CWS is to detect contamination incidents in time to reduce potential public health and economic consequences. To address the second step of the protocol, researchers are developing source identification methods (Shang et al., 2002; van Bloemen Waanders et al., 2003; Laird et al., 2006; Preis and Ostfeld, 2006; De Sanctis et al., 2006; De Sanctis et al., 2008) to identify contaminant injection locations following successful detection of a contamination event.

Should a CWS detect the presence of a contaminant in a water distribution network, the third step in the protocol, consequence management, must be employed. A variety of response actions must be examined in order to select the most beneficial consequence management strategy, including public notifications and operational changes. A relatively common operational response option utilized by water utilities to address water quality concerns is flushing. Previous research efforts (Baranowski and LeBoeuf 2008) used hydraulic/water quality modeling and optimization tools to guide the selection of hydrant locations to flush and valves to close. The selection was based on minimizing the impact of a contamination incident in a water distribution system. In previous work, the contaminant injection location was assumed known prior to the implementation of a flushing strategy. However, during a real contamination incident, utility personnel might not have prior knowledge of the injection location. In this current research effort, the effect of knowing the injection location prior to response activities is evaluated. Combining all three steps of the protocol together, three different methods to identify the contamination source in the example network are utilized.

2. METHODOLOGY

The objective of this research is to identify hydraulic responses that reduce the impact of a contamination event on a water distribution network following successful detection and source identification. Using a single network model, EPANET, fixed sensors, and a genetic algorithm, two contamination incidents are simulated and three strategies for identifying the contaminant injection location are used to compare the performance of each flushing strategy.

Since in an actual contamination event the injection location of a contaminant which triggers an alarm at a sensor will most likely not be known accurately in real time, three methods to identify the source injection location were utilized: known, backtracking, and sensor coverage map. In the known approach, the contaminant injection location is known prior to the start of any response actions. This type of approach would be applicable if a criminal informed the water utility of the location or if clear evidence was found at the site. In general, this approach would lead to most effective consequence management strategy. In this paper, this approach is used as the baseline for the reduction in impact. The other two approaches, backtracking and sensor coverage map, are explained in more detail below. Once the contamination source location(s) have been identified, this information is supplied to an optimization routine which minimizes the impact(s) by selecting nodal locations to flush the contaminant out of the distribution network.

2.1 Backtracking

In the backtracking approach, simulated contaminant concentrations at the monitoring locations and the contamination status algorithm (CSA) proposed by De Sanctis et al. (2009; 2006) were used to determine possible contamination source locations. By using a particle backtracking algorithm (Shang et al., 2002), as implemented in the pre-release version of EPANET-BTX (a backtracking extension to EPANET), to establish network flow paths, the CSA identifies all the possible contamination sources in space and time. The CSA assigns a contamination source status to each node-time pair: candidate (possible contamination source), safe (not a possible contamination source), or unknown (insufficient information to classify the source). Using the candidate status as an indicator, the possible contamination sources were determined.

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2.2 Sensor Coverage Map

For the sensor coverage map approach, the Threat Ensemble Vulnerability Assessment – Sensor Placement Optimization Tool (TEVA-SPOT) was used (U.S. EPA, 2009). Using fixed online sensor locations, contamination incidents at all of the nodes in the network were simulated and health impacts were calculated in TEVA-SPOT. A table in TEVA-SPOT lists the impacts, detection times, and detection sensor for all of the simulated incidents. With this information, the possible contamination sources to trigger an alarm at each sensor can be determined. This approach assumes that response actions are implemented immediately after the first alarm.

2.3 Optimization of Flushing Decisions

The optimization approach utilized has been modified from the method proposed by Baranowski and LeBoeuf (2008). The same genetic algorithm within MATLAB (MathWorks, 2008) was utilized to minimize the impacts of a contamination event by optimally selecting different flushing locations, however, the framework to simulate the incidents and calculate the impacts is different. Instead of using EPANET toolkit function calls, components of the TEVA-SPOT Toolkit (Berry et al., 2009) which simulate contamination incidents and assess consequences were employed. In order to be applicable for response applications, the TEVA-SPOT components had to be modified. The component which simulates contamination incidents was modified to alter demands at node locations identified as hydrants. The component which assesses consequences was modified to include a new impact metric which is used here as the optimization objective. The new metric is extent of contamination over a specified period of time. The extent of contamination in the network was calculated for all pipes and times until the end of the simulation. The extent of contamination is calculated as follows:

$$ExtentContamination = \sum_{\substack{i=1..N \\ j=t_{beg}..t_{end}}} contLength_{i,j}$$

where i is the pipe number, N is the total number of pipes, *contLength* is the length of contaminated pipe, and j is time from the beginning of the simulation, t_{beg}, until the end of the simulation, t_{end}. The contaminated pipe length is determined as the entire length of pipe if the concentration in the pipe is greater than zero. This metric is used since it captures all of the time steps in which a pipe is contaminated and allows the pipe to become uncontaminated and re-contaminated in different time steps, assuming that the contaminant does not adsorb to the pipe wall. Other metrics of contamination effect could be utilized.

3. EXAMPLE

The example network utilized was Network 1 from the Battle of the Water Sensor Networks (BWSN) (Ostfeld et al., 2008), which consists of 126 nodes, one reservoir, two tanks, two pumps, eight valves, and 170 pipes (Figure 1). For this paper, sensors were located at Junctions 17, 21, 68, 79, and 122 (green stars in Figure 1) as determined by Berry et al. in the BWSN (Ostfeld et al., 2008). For purposes of simulation, a conservative contaminant with a mass injection rate of 8330 mg/min was injected at hour 168 of the simulation for one hour. The overall simulation time was 336 hours, which captured the majority of the contamination spread. The initial simulation ran until detection by one of the sensors, where detection was considered as a concentration greater than 0.01 mg/L.

Starting two hours after detection of the contaminant, flushing was initiated for eight hours. Two hours is an optimistic time period in which to confirm that contamination is occurring, estimate the possible source locations and spread of the plume, determine the best hydrants to flush, mobilize the necessary crews and have them travel to the sites. This response time delay was chosen since it leads to a conservative estimate on the reduction of impacts. For the purpose of this paper, a maximum of 10 flushing locations were chosen by the optimization algorithm. This number seemed reasonable based on information obtained from a partnering, middle-sized water utility, which stated that to avoid depressurization in their system, the maximum number of hydrants that can be flushed simultaneously is ten (Baranowski et al., 2008). The flushing discharge rate was set at 3.03 m^3/min (800 gpm).

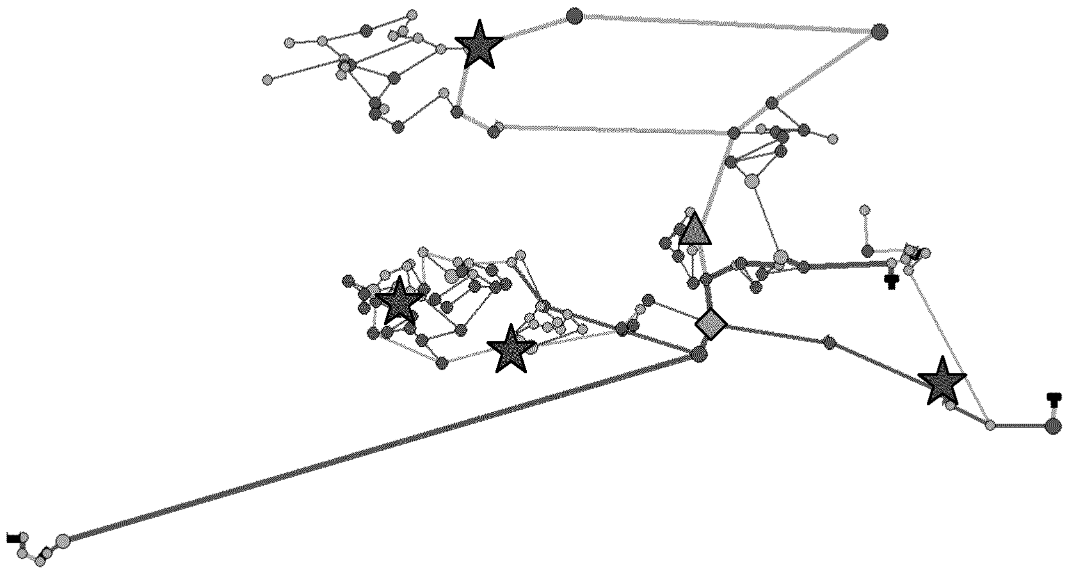

Figure 1. Schematic of BWSN Net 1. Colored links represent different diameter pipes, with thicker lines being larger diameters. Colored nodes represent different base demands, with larger nodes being larger demands. The green stars denote the sensor locations, the blue triangle is the injection location for Scenario 1, and the purple diamond is the injection location for Scenario 2.

4. RESULTS

The first injection scenario, Scenario 1, was initiated at Junction 21 (blue triangle in Figure 1), while the second injection scenario, Scenario 2, was initiated at Junction 23 (purple diamond in Figure 1). The scenarios were selected since they were detected relatively quickly (i.e., within two hours of the injection) by the fixed sensor locations. Scenario 1 was detected by the sensor at Junction 21 at hour 168 with a concentration of 2.96 mg/L. Scenario 2 was detected by Junction 68 at hour 170 with a concentration of 0.71 mg/L. For each injection scenario, the concentrations at each sensor and for each time step were determined. This concentration matrix was supplied to the contamination source algorithm. Using the flush start time for each scenario, the junctions that could have been sources at hour 168 in the simulation are identified for the backtracking source approach. For the sensor coverage map approach, TEVA-SPOT was used to identify all of the contamination events which could be detected by each of the sensors. Table 1 lists all of the possible source locations for the three source methods and the two scenarios.

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Table 1. Source location junctions identified by three methods (known, backtracking, and sensor coverage) for two injection scenarios.

Scenario	Known Source	Backtracking Source	Sensor Source
1	21	20, 21	21, 22, 24, 25, 26, 27, 28, 43, 47, 48, 49, 50, 51, 52, Tank 130
2	23	23, 30, 33, 53, 55, 56, 63, 64, 67, 90, 91, 92	23, 30, 31, 53, 54, 55, 56, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68

The source locations listed in Table 1 were supplied as input to the optimal flushing method, which minimized the average impact across all of the injection locations. A total of six different optimal runs were completed. Each optimization analysis ran for 51 generations with a population of 50, for a total of 2600 simulations including the initial population simulation. The genetic algorithm selected the number of locations flushed and the locations to flush. The maximum number of locations that could be flushed was set at 10. All of the junctions in the model, or 126 locations, could be used as flushing locations. The flushing locations selected for the six optimizer runs are listed in Table 2. Each of the runs chose at least six locations to flush, with half of the runs selecting the upper limit of 10 locations.

Table 2. Flushing junctions selected for two scenarios and three source identification approaches.

Scenario	Known Source	Backtracking Source	Sensor Source
1	10, 11, 12, 13, 100, 111	14, 89, 93, 104, 125, 126, 128	5, 19, 30, 52, 54, 59, 71, 74, 82, 123
2	3, 7, 13, 23, 31, 47, 52, 63, 81, 91	33, 35, 48, 49, 63, 71, 79, 81, 99, 114	16, 57, 65, 81, 82, 83, 86

Table 3 lists the percent reduction in the impact measure from the base case of no flushing. For scenario 1, the known source approach achieved the greatest reduction in impact of 98%; with the backtracking approach having a similar percent reduction of 84%. Using the sources identified in the backtracking approach had better results than the sensor coverage map approach. The sensor coverage map approach had the lowest reduction in impact with 21% reduction. Since scenario 1 was detected early, a greater reduction in the impact was achievable. Scenario 2 was detected later; therefore, the impact was only reduced by 47% for the known source approach. The backtracking source and the sensor coverage map approaches were only able to reduce the impacts by about 2%.

Table 3. The percent reduction in the extent of contamination for the two scenarios and three source identification approaches.

Scenario	Known Source	Backtracking Source	Sensor Source
1	98.5	83.7	20.9
2	47.4	2.4	1.8

While the flushing locations selected for the backtracking and sensor coverage map approaches reduced the impacts by the percentages shown in Table 3, these locations might be able to reduce the impacts associated with the other identified source locations by a greater percentage. For the backtracking approach, the identified source locations and their associated impact reductions for each scenario are listed in Table 4. The average impact reduction was 90% and 76% for scenarios 1 and 2, respectively. For scenario 1, the average impact was reduced by 90%, while the true source location was reduced by 84%. Eight of the identified source locations for scenario 2 were reduced by at least 80%. Unfortunately, the true source location was only reduced by less than 2%.

Table 4. For the backtracking approach, the reduction percentage for each of the identified source locations.

Scenario 1	
Source Location	**Percent Reduction**
JUNCTION-20	95.91
JUNCTION-21	83.71
Average	89.81

Scenario 2	
Source Location	**Percent Reduction**
JUNCTION-23	2.39
JUNCTION-30	94.36
JUNCTION-33	52.65
JUNCTION-53	80.37
JUNCTION-55	85.76
JUNCTION-56	87.75
JUNCTION-63	97.88
JUNCTION-64	97.47
JUNCTION-67	98.23
JUNCTION-90	75.22
JUNCTION-91	92.25
JUNCTION-92	42.58
Average	75.58

For the sensor coverage map approach, the optimization routine reduced the average impact by at least 50%. Table 5 lists the source locations identified by this approach and their associated reduction in impact for each scenario. For scenario 1, five of the identified source locations were reduced by at least 98%, however the true source location was only reduced by 21%. Sixteen of the identified source locations were reduced by at least 96%, while the true source location was reduced by less than 2% for scenario 2.

Table 5. For the sensor coverage map approach, the reduction percentage for each of the identified source locations.

Scenario 1	
Source Location	**Percent Reduction**
JUNCTION-21	20.87
JUNCTION-22	3.19
JUNCTION-24	78.47
JUNCTION-25	79.14
JUNCTION-26	2.26
JUNCTION-27	3.72
JUNCTION-28	2.18
JUNCTION-43	59.65
JUNCTION-47	79.74
JUNCTION-48	99.68
JUNCTION-49	98.62
JUNCTION-50	99.98
JUNCTION-51	98.32
JUNCTION-52	97.99
TANK-130	1.46
Average	51.91

Scenario 2	
Source Location	**Percent Reduction**
JUNCTION-23	1.78
JUNCTION-30	99.15
JUNCTION-31	96.66
JUNCTION-53	97.49
JUNCTION-54	97.19
JUNCTION-55	96.83
JUNCTION-56	97.85
JUNCTION-58	56.43
JUNCTION-59	99.27
JUNCTION-60	99.30
JUNCTION-61	98.75
JUNCTION-62	98.96
JUNCTION-63	97.68
JUNCTION-64	96.89
JUNCTION-65	97.36
JUNCTION-66	96.23
JUNCTION-67	98.01
JUNCTION-68	97.63
Average	70.97

5. CONCLUSIONS

Following successful detection by a CWS, actions to reduce the impact of a contamination event must be implemented. One response action which can be implemented relatively quickly is flushing. To increase the effectiveness of the flushing strategy, the most beneficial hydrants should be selected. Knowing the contaminant injection location and network hydraulics prior to the start of any flushing strategy could assist the water utility in selecting better hydrant locations to remove the contaminated water from the network. For this research effort, an optimization tool linked with a hydraulic/water quality model was utilized to select the hydrant locations. The optimization tool was supplied with contaminant injection locations identified by three different approaches: a known source, sources determined by a backtracking tool, and sources determined by a sensor coverage map.

The three source location approaches resulted in different reductions of the impact. Knowing the source location resulted in the greatest reduction in the impact measure, while the flushing locations selected from the sensor coverage map approach decreased impacts by less than 20%. Overall, knowing the contaminant injection location greatly influences the effectiveness of the flushing response (Tables 3, 4, and 5). For this example network, when online water quality sensor measurements from a CWS are linked with a backtracking tool and optimal hydraulic response tool, the greatest reduction in the impact of contamination event were achieved. To explore the applicability of this approach to real world systems, larger water distribution networks, such as the BWSN Network 2 and real world utility networks, will be used in future studies. In addition, a variety of injection locations and impact measures will be explored. Instead of minimizing the average impact over all possible sources, another objective function could maximize the minimum performance over all possible sources.

Disclaimer

This project has been subjected to the U.S. Environmental Protection Agency's review and has been approved for publication. The scientific views expressed are solely those of the authors and do not necessarily reflect those of the U.S. EPA. Mention of trade names or commercial products does not constitute endorsement or recommendation for use.

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